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Citation for published version:
Gorbachev, O 2011, 'Did household consumption become more volatile?', *American Economic Review*, vol. 101, no. 5, pp. 2248-2270. https://doi.org/10.1257/aer.101.5.2248

Digital Object Identifier (DOI):
10.1257/aer.101.5.2248

Link:
Link to publication record in Edinburgh Research Explorer

Document Version:
Peer reviewed version

Published In:
American Economic Review

Publisher Rights Statement:
©Gorbachev, O. (2011). Did household consumption become more volatile?. American Economic Review, 101(5), 2248-2270. 10.1257/aer.101.5.2248

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Download date: 07. May. 2023

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Gorbachev, O. (2011). Did household consumption become more volatile?. American Economic Review, 101(5), 2248-2270,
doi: 10.1257/aer.101.5.2248

Did Household Consumption Become More Volatile?*

[Accepted for publication by AER]

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May 26, 2010

Abstract

I show that after accounting for predictable variation arising from movements in real interest rates, preferences and income shocks, liquidity constraints and measurement errors, volatility of household consumption in the US increased by 23.5 percent between 1970 and 2004. The increase was lower than that of volatility of family income. However, nonwhite households and household with less than 13 years of education, for whom there was no differential increase in income volatility, experienced significantly larger increase in volatility of household consumption. The effect of race and education remained significant even after income, working history, marital status, family size and composition were controlled for. Substantial differences in wealth and access to credit markets point to the main reason for this divide.

Keywords: panel data, Euler estimation, consumption risk, racial divide

JEL Classification: D80, D91, E21

*I am grateful to Orazio Attanasio, Brendan O'Flaherty, and Bernard Salanié for their unwavering support and engorgements, and seminar participants at 2007 NBER Summer Institute on Aggregate Implications of Microeconomic Consumption Behavior, The Board of Governors of the Federal Reserve System, Columbia University, McGill University, University College London, and University of Edinburgh for their constructive criticism and very useful comments and suggestions. I would also like to thank Keshav Dogra and Felix Pretis for their excellent research assistance, and the University of Edinburgh for its financial support.

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1 Introduction

By now it is well documented that volatility of male earnings increased substantially from the 1970s to early 1980s, was stable in the 1980s to early 1990s, and began to increase again since the mid 1990s.[1] Volatility of family income, both its permanent and transitory components, also increased since the 1970s.[2]

Greater income uncertainty, however, may not necessarily translate into welfare losses if people can find ways to smooth consumption. Having a good measure of the volatility of household consumption is thus fundamental to assessing whether, and to what extent, welfare was affected by increased income shocks. In this paper, I provide a novel way to compute household level volatility of consumption. I use an incomplete markets consumption model[3] with nonseparable preferences for food and other nondurable goods, controlling for measurement error in consumption and liquidity constraints. I estimate volatility of consumption using Panel Studies of Income Dynamics (PSID) data.[4] I find that after accounting for predictable variations in consumption due to changes in family composition and structure, real interest rates, income uncertainty and cash on hand (as a proxy for precautionary savings), and after controlling for measurement error in consumption, nonseparability of preferences, and liquidity constraints, mean volatility of household food consumption increased by 43 percent between 1970 and 2004. This is a conservative estimate since food consumption is

[1]See for example, Moffitt and Gottschalk [1994, 1998, 2002], Dynarski and Gruber [1997], Haider [2001], Hacker [2006], Dynan et al. [2007], Keys [2008], Shin and Solon [2008], Jensen and Shore [2008].

[2]See for example Dynan et al. [2007], Keys [2008], Shin and Solon [2008], and Jensen and Shore [2008].

[3]There are many studies documenting that financial markets are incomplete. For example, a recent paper by Blundell et al. [2008] finds some partial insurance of permanent shocks, especially for the college educated and those near retirement, and full insurance of transitory shocks except among poor households. Other examples include: Cochrane [1991], Attanasio and Davis [1996], Krueger and Perri [2006], and many others.

[4]Another frequently used source of consumption data on household level, Consumer Expenditure Survey, is unsuitable for this study as it has a very short time dimension of only four quarters. I don't use CES data directly to compute my measures of consumption volatility. Instead I use CES data to estimate elasticity of food with respect to nondurables for all available years of data, allowing elasticities to change over time, and then compute the evolution of nondurable consumption based on these estimates.

well known to have low income elasticity.[5] In fact, using estimates of elasticity of food with respect to other nondurables, I find that volatility of nondurable consumption went up by 51 percent. If, in addition, measurement error fell over this period, the increase in volatility might still be an underestimate.[6]

For households headed by nonwhite and poorly educated individuals, the rise in volatility was significantly larger than for the average household. Race did not play a significant role in the way income volatility increased over the period. On the other hand, households whose head was nonwhite experienced a significantly larger increase in volatility of consumption than that endured by white households, a rise of 53 percent vs. that of 25 percent, respectively. Education also played an important role. Households with lower education had a smaller increase in volatility of income than households with more than 12 years of education, on the other hand, volatility of consumption for these households increased by much more, by 47 vs. 17 percent, respectively. Even though the increase in consumption volatility was significantly smaller than that of family income uncertainty over the same period, household volatility of income doubled, the cost to society from this rise was significant. Using the simplest back of the envelope calculation, I find that an average household would be willing to sacrifice 4.15 percent of their annual nondurable consumption to reduce consumption risk back to where it was in 1971.[7]

The most relevant to this paper strand of literature estimates the response of consumption to income shocks. Jappelli and Pistaferri [2010] provide a comprehensive review on the state of this research. They document that there is considerable evidence that consumption

[5]See for example, Bunkers and Cochrane [1957].

[6]It is reasonable to believe that the measurement error fell in the sample due to increased household's duration in the survey, reduction in recall period from 1 year to 1 week, technological innovation in the survey collection.

[7]I use a simple formula derived from Lucas [1987], where the cost of business cycle can be approximated by $\mu = \frac{1}{2}\gamma\sigma_c^2$. Volatility of household food consumption was 0.087 in 1971 and went up to 0.147 by 2004. My estimate of relative risk aversion $\gamma = 1$. Thus, the cost is 3 percent of household food consumption per year. Since, the elasticity of food expenditure with respect to expenditure on nondurables is 0.85, consumers would be willing to sacrifice 4.15 percent of annual nondurable consumption to lower risk to its 1971 level.

appears to respond to anticipated income increases, over and above by what is implied by standard models of consumption smoothing, and that at least to some extent, liquidity constraints are an important culprit for this failure. A second finding that emerges from the literature is that consumption reaction to permanent shocks is much higher than that to transitory shocks. There is also evidence, at least in the US, that consumers do not revise their consumption fully in response to permanent shocks. In fact, Carroll [2009], shows that if consumers are impatient and are subject to transitory as well as permanent shocks, the optimal marginal propensity to consume out of permanent shocks is strictly less than one, because buffer-stock savers have a target wealth-to-permanent-income ratio; a positive shock to permanent income moves the ratio below its target, temporarily boosting saving. Taken together, these finding are consistent with the hypothesis that precautionary savings and even perhaps insurance over and above self-insurance (achieved through government welfare programs, family labor supply, or family networks) play an important role in consumption.

From Jappelli and Pistaferri [2010] survey, it is clear that a lot of thought and effort has gone into understanding how consumption responds to income shocks. But, there are few studies that analyze *the change* in the ability of households to respond to income shocks. Recent work by Blundell et al. [2008] studies changes in the joint distribution of income and consumption between 1980 and 1993. By studying the link between consumption and income inequality, the authors find that household's ability to insure against income shocks has remained unchanged.

To my knowledge, the only other paper that examines changes in volatility of household consumption is by Davis and Kahn [2008]. Using data from Consumer Expenditure Survey for 1980-2004, which has a short panel dimension - 4 quarters of data over one year, the authors compute volatility of consumption as absolute value of log change in nondurable consumption expenditures for each household, as a difference between 1st and 4th quarter consumption, and then average over households for each year of data. They also find that volatility of total nondurable consumption increased between 1980 and 2004. However, their measure of volatility based on raw consumption data is purely descriptive and might suffer from measurement error, it might be incorrectly attributing an increase in their measure to volatility, when indeed the increase is due to increased skill premium or simply life-cycle considerations, preference shocks, or differences in discount factors across individual households. Changes in theses predictable components will have different welfare implications from changes in consumption due to household's inability to smooth shocks due to uncertainty of any kind.[8] Another consideration that should be taken into account when using CES data is that the survey has become much less reliable over the years as it highly underestimates nondurable consumption.[9] There are no such claims regarding PSID's admittedly scarce consumption data. In addition to these considerations, the study presented here provides detailed decomposition results by race, education, income and marital status absent in the Davis and Kahn [2008] paper. There are significant differences observed between races and educational groups that should not be overlooked when designing policy prescriptions.

The aim of this paper is to understand the link between income and consumption *volatility*. There is already a very large literature that tries to understand the link between income and consumption *inequality*.[10] It is important to mention that the two concepts, even though related, are not the same.[11] The main difference between the two is that one deals with re-

[8]For example, changes in consumption due to preference shocks, such as for example in expectation of kids living/arriving home will appear as increase in volatility according to Davis and Kahn [2008] measure. Clearly, these types of changes are not due to uncertainty and should not have the same welfare implications as changes in consumption due to unexpected loss of a job or an unexpectedly high health care bill.

[9]Battistin [2004], Attanasio et al. [2004], and Battistin and Padula [2009] have documented that the gap between the Personal Consumption Expenditure and CES nondurable consumption data has been growing since 1990.

[10]See for example, Baker [1997], Gottschalk [1997] Moffitt and Gottschalk [1994, 2002], Katz and Autor [1999], Blundell and Pistaferri [2003], Gyourko and Tracy [2003], Storesletten et al. [2004], Attanasio et al. [2004], Krueger and Perri [2006], Blundell et al. [2008], Davis and Kahn [2008], Gordon and Dew-Becker [2008], Keys [2008], Primiceri and vanRens [2009], Heathcote [2009].

[11]It is possible to come up with examples where inequality is rising in the society, but volatility is zero or unchanged, and vice versa. Take an economy with 2 types: one who starts out poor and whose income grows at 1 percent per year, and another, who starts out rich and whose income grows at 2 percent per year. Inequality in this economy will be growing over time, but volatility will be zero and unchanging. Introducing aggregate and/or idiosyncratic shocks (idiosyncratic shocks that come from the same distribution), indepen-

source allocations and/or inequity and the other with individual intertemporal decisions. Thus the two concepts are typically addressed using different analytical frameworks. More importantly, evolution of inequality and volatility may have different welfare implications. Addressing welfare implications from increased inequality is complex because of social preferences or interpersonal competition.[12] On the other hand, since the aim of households is to minimize variability of consumption, reduction in volatility would be highly beneficial. Therefore, a study of intertemporal properties of household consumption and income will add to our understanding of the changes affecting households and their ability to cope with these changes now versus 30 years ago.

2 Volatility of Household Income

As the first step towards understanding changes in household welfare, I look at the evolution of income volatility over the 1970-2004 period. As in Blundell et al. [2008], I assume that the income process for each household h is given by:

$$ln(Y_{h,a,t}) = Z'_{h,a,t}\vartheta_t + P_{h,a,t} + \nu_{h,a,t} \tag{1}$$

where a and t index age and time respectively, Y is real income, and Z is a set of income characteristics observable and anticipated by consumers, that is allowed to change over time. In individual labor income models, these regressors are usually proxied by age, age squared, dummy variables for education, occupation and industry categories, and interactions between age, age squared and education, sex and race indicators, cohort dummies, time dummies (to control for aggregate shocks), and interaction terms. Since in the present case we are interested in the family income process, I redefine these parameters as those pertaining to the head of household, and include additional parameters, such as head's marital status,

dent of correlation of these shocks, will not change this result. Getting rid of heterogeneity will mean the end to inequality. But even with increasing inequality, volatility might not change or even fall, as evolution of volatility depends on the change in the size and correlation of the shocks affecting households.

[12] See for example work by Sen [1980].

number of hours worked by head and his partner, and the number of children and adults in the household. I also control for cohort effects.[13] Equation (1) decomposes the remainder of income into a permanent component $P_{h,a,t}$, which follows a martingale process of the form: $P_{h,a,t} = P_{h,a,t-1} + \varsigma_{h,a,t}$, where $\varsigma_{h,a,t}$ is serially uncorrelated; and the transitory mean-reverting component, $\nu_{h,a,t}$.[14]

The volatility of income, $\sigma^2_{h,a,t}$ is then measured as a square of the unexplained income growth component, which is composed of household specific time varying shocks to permanent and transitory income.

$$\sigma^2_{h,a,t} = \Big(\varsigma_{h,a,t} + \Delta\nu_{h,a,t}\Big)^2 = \Big(\Delta ln(Y_{h,a,t}) - \Delta\widehat{ln(Y_{h,a,t})}\Big)^2 \tag{2}$$

I assume that households are unable to distinguish between these shocks, or that when a household observes a shock to income, he is unable to distinguish between the two different shocks, or to disentangle the size of each shock.

Before looking at the actual volatility of income, it is useful to quickly describe the data. I use Panel Study of Income Dynamics data for 1968-2004 period. I keep households whose head was between the age of 25 and 65, was not retired, was not a student, was not from Immigrant or Survey of Economic Opportunity sample, and who had positive food consumption expenditure.[15] For the reasons that will become apparent in the next section, I keep only households who I classify as liquidity unconstrained, based on their level of non-housing wealth. In 2004, average household was 43 years old, had 1 child, was 17 percent likely headed by a female, was 10 percent likely to be nonwhite, 72 percent likely to be married and 6 percent likely to be a single parent. Average family income in 2004 was \$50,183 and average non-housing net wealth was \$136,203; with 76 percent of households owning a home, average home value was \$195,349. On average, households spent 8 percent of their income on food expenditures.

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[13]The importance of including cohort effects is highlighted, in for example Blundell et al. [2008].

[14]This is a standard model of the income process, see for example MaCurdy [1982], Hall and Mishkin [1982], Abowd and Card [1986], Moffitt and Gottschalk [1994]; or Banks et al. [2001] and Meghir and Pistaferri [2004] for more recent studies.

[15]Appendix provides detailed explanation on how the data sample was created.

These averages mask dramatic differences within income distribution even for liquidity unconstrained households. Households whose real family income in 2004 was less than or equal to \$11,504 (or \$9,140 per effective person, p.e.p.[16]) were in the bottom 20 percent of the income distribution.[17] These households spent about 27 percent of their income to cover food consumption; and had on average \$28,492 in non housing net wealth. The median of the income distribution was at \$35,408 (\$22,420 p.e.p.). A median household spent about 11 percent of their income on food in 2004, though this ratio was much higher at 17 percent in 1970. Non housing wealth for the median household was at \$81,760. Households whose real incomes were at or above \$111,973 (\$63,274 p.e.p.) were the richest 20 percent. They spent only 6 percent of their income on food consumption, and had \$345,840 in non housing wealth. These statistics illustrate acute differences observed in our sample, and these differences will play an important role on how income volatility affected household welfare.

Figure 1 illustrates evolution of the mean of $\sigma^2_{h,a,t}$ and its 90/10 percentile ratio for annual and biennial samples.[18] It is clear that volatility of family income increased substantially since the beginning of the period. Computed on annual data, which is available from 1968 to 1996, volatility rose steadily between 1970 and 1986, increasing by 65 percent; it dipped between 1986 and 1991, falling by 15 percent; and then began rising again. The 90th percentile of volatility series almost doubled between 1970 and 1996, rising gradually between 1970 and 1991, by 15 percent; and then shooting up from 0.30 to 0.54 by 1996. The 10th percentile, on the other hand, was flat over the entire period, contributing to the differential trends between the mean and the 90/10 percentile ratio.

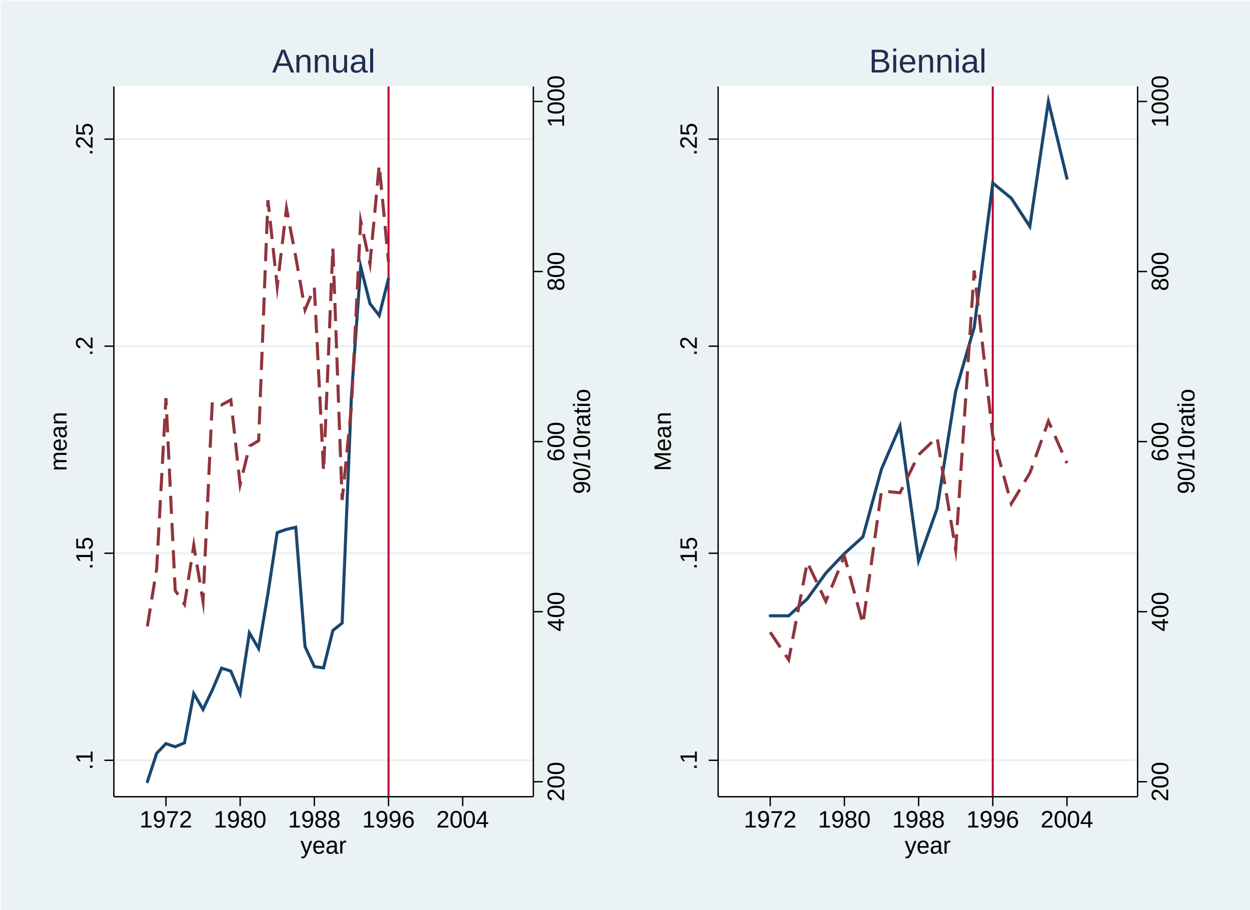
Family income volatility in the biennial sample also increased over the period. Figure 1 clearly shows that this increase continued until 2004. A comparison of biennial and annual data series illustrates that there were no differences in patterns between the mean volatility

[16]To convert family income into effective units, I divide family income by the square root of the size of the household.

[17]Since family income is a sum of labor, rental, business and asset income, it can be zero or even negative.

[18]Biennial volatility is computed as: $\sigma^2_{h,a,t} = \left(ln(Y_{h,a,t}) - ln(Y_{h,a,t-2}) - ln(\widehat{Y_{h,a,t}}) - ln(\widehat{Y_{h,a,t-2}})\right)^2 = \left(\varsigma_{h,a,t} + \varsigma_{h,a,t-1} + \nu_{h,a,t} - \nu_{h,a,t-2}\right)^2$

Figure 1: Volatility of Family Income



Legend Key: Long-dash is for 90/10 percentile ratio, and solid is the mean of volatility of family income, $\sigma^2_{h,a,t}$, based on equation (2).

Note: Annual graph is based on annual growth rates data sample, and biennial graph on the biennial growth rates, such as

$$\sigma^2_{h,a,t} = \left(ln(Y_{h,a,t}) - ln(Y_{h,a,t-2}) - ln(\widehat{Y_{h,a,t}}) - ln(\widehat{Y_{h,a,t-2}})\right)^2 = \left(\varsigma_{h,a,t} + \varsigma_{h,a,t-1} + \nu_{h,a,t} - \nu_{h,a,t-2}\right)^2$$

and that of 90/10 percentile ratio between 1970 and 1996. After 1996, the 90/10 ratio fell significantly whereas the mean continued to rise. These differences come from the fact that the 10th percentile rose dramatically over 1996-2004 period, climbing from 0.0007 in 1996 to 0.0011 by 2004.

These findings are very close to those obtained by Dynan et al. [2007], who document that family income volatility increased since the 1970s, and in particular since the 1990s. They show that the probability of large increases in income (larger than 25%) increased from on average 9% between 1970 and 1990, to 15% by 2002; though this probability fell back to 9% by 2004. At the same time, probability of getting a large negative shock (larger than 25%) was stable around 9% until late 1990s, it increased substantially to almost 14% by 2004.

Increase in income volatility does not necessarily translate into higher welfare costs as members of household can smooth consumption by adjusting their working hours, borrowing or utilizing their savings. Thus, to analyze whether household's welfare was affected by increased income uncertainty, I examine the evolution of variability of household consumption.

3 A Consumption Model

In order to construct a measure of volatility of consumption, I first take out predictable variations in consumption, by using a permanent-income hypothesis model under imperfect financial markets, and then construct volatility as a square of the unpredictable component. Computing volatility of consumption on raw data is unsuitable when one is concerned with welfare calculations. Changes in consumption growth due to predictable components, such as for example due to changes in preferences or precautionary savings, will have different welfare implications from changes in consumption due to household's inability to smooth shocks due to uncertainty of any kind. In the absence of perfect insurance, households are unable to insure against income shocks, with the consequence that an increase in unanticipated risk would directly increase volatility of consumption especially if households have limited ability to smooth out these shocks. Since families desire to smooth consumption, such an increase in volatility would have a negative impact on welfare, other things being equal.

Consumption growth varies with preferences or demographics, the risk free interest rate, anticipated income shocks, cash-on-hand relative to future wealth, and idiosyncratic risk.

To see this, consider a typical Euler equation.

$$E_t\left[\frac{U'(C_{h,t+1};\theta_{h,t+1})(1+r_{h,t+1})(1+\lambda_{h,t+1})}{U'(C_{h,t};\theta_{h,t})(1+\delta_h)}\right]=1 \tag{3}$$

where h stands for household and t for time; $C_{h,t}$ is real consumption of family h in period t; $\theta_{h,t}$ are family $h's$ tastes; δ_h is its rate of time preference and is assumed to be household specific but time invariant; E_t is the expectation operator, conditional on information available at time t; $r_{h,t+1}$ is the ex post real return on risk free asset held by family h between periods t and $t+1$; $\lambda_{h,t+1}$ is the extra utility that would result from borrowing an extra dollar, consuming it, and reducing consumption the next period accordingly to repay the debt. If $\lambda_{h,t+1}>0$, the liquidity constraint is binding and the family cannot borrow as much as it wants, and thus will have to consume out of current assets.

In order to allow for precautionary savings and nonseparability of preferences between consumption of food and other nondurables,[19] and to be able to take the model to the data, I assume that the utility function takes the constant relative risk aversion form, such that

$$U(O_{h,t},F_{h,t};\theta_{h,t})=e^{\theta_{h,t}}\left[\frac{O^{\alpha}_{h,t}F^{\beta}_{h,t}}{1-\gamma}\right]^{1-\gamma} \tag{4}$$

where $F_{h,t}$ is food consumption and $O_{h,t}$ is consumption of other nondurable goods, such that $p^F_t F_{h,t}+p^O_t O_{h,t}=C_{h,t}$; α and β are share parameters measuring the importance of consumption of other nondurable goods relative to food and visa versa; and γ controls the degree of relative risk aversion.[20]

Using the above functional form for the utility function, rational expectations, and taking 2nd order Taylor approximation of the above Euler equation,[21] the growth rate of household

[19] As pointed out by example Attanasio and Weber [1995], Meghir and Weber [1996], Banks et al. [1997] it is important to control for nonseparability of food consumption relative to consumption of other goods.

[20] The coefficient of relative risk aversion with this utility specification is given by $\frac{-FU_{FF}}{U_F}=1-\beta(1-\gamma)$. Intertemporal elasticity of substitution for food consumption is pinned down by $\frac{1}{\beta(1-\gamma)-1}$.

[21] Attanasio and Low [2004] show that a log-linearized Euler equation for consumption yields consistent estimates of the preference parameters when utility is isoelastic and a sample covers a long time period. The requirement on the length of the panel is imposed in order to tackle estimation problems that arise due to the presence of liquidity constraints.

food consumption, $\Delta ln(F_{h,t+1})$, is a function of anticipated changes in demographics or preferences $\Delta\theta_{h,t+1}$, risk free interest rate $ln(1+r_{h,t+1})$, the shadow price of borrowing an extra dollar $ln(1+\lambda_{h,t+1})$, personal discount rate $ln(1+\delta_h)$, inflation in food prices, Δlnp^F_{t+1}, inflation differential between food and other nondurables, $\Delta lnp^O_{t+1} - \Delta lnp^F_{t+1}$, precautionary saving motive, $V_t\epsilon_{h,t+1}$, and idiosyncratic shocks to consumption growth, $\varsigma_{h,t+1}$.

$$\begin{aligned}
\Delta lnF_{h,t+1} &= \frac{1}{1-(1-\gamma)(\alpha+\beta)}\Big[\Delta\theta_{h,t+1} + ln(1+r_{h,t+1}) + ln(1+\lambda_{h,t+1}) + ln(1+\delta_h)\Big] \\
&- \frac{1}{1-(1-\gamma)(\alpha+\beta)}\Big[\Delta lnp^F_{t+1} + \alpha(1-\gamma)(\Delta lnp^O_{t+1} - \Delta lnp^F_{t+1})\Big] + z_{h,t+1} \qquad (5) \\
\texttt{where} & \\
z_{h,t+1} &= \frac{\alpha(1-\gamma)-1}{(1-\beta(1-\gamma))(1-(1-\gamma)(\alpha+\beta))}\Big[\varsigma^F_{h,t+1} - \frac{V_t\epsilon^F_{h,t+1}}{2}\Big] \\
&- \frac{\beta\alpha(1-\gamma)^2}{(1-\beta(1-\gamma))(1-(1-\gamma)(\alpha+\beta))}\Big[\varsigma^O_{h,t+1} + \frac{V_t\epsilon^O_{h,t+1}}{2}\Big] \\
&= \varsigma_{h,t+1} - \frac{V_t\epsilon_{h,t+1}}{2}
\end{aligned}$$

It is well known that consumption is measured with error. To control for this error, I follow Alan et al. [2005] in assuming that measurement error is stationary and independent of all the regressors, including lagged values of the measurement error and expectations error, consumption levels and interest rates.[22] The error term, $z_{h,t+1}$ contains

When liquidity constraints are not binding, $\lambda_{h,t+1} = 0$, and equations (5) is simplified. If liquidity constraints are ignored, then their presence will show up in the error term.[23] Since PSID does not proved direct measures of liquidity constraints, I classify households

[22]These assumptions mean that the expected growth rate of the measurement error is zero, and its variance is a constant, which could be households or group specific.

[23]It is important to control for liquidity constraints as otherwise coefficient estimates will be biased. In addition, if liquidity constraints are changing over time, estimates of consumption volatility might pick up those changes rather than actual estimates of consumption uncertainty. The risk of this is small, since recent work by Dogra [2009], who used data from Survey of Consumer Finances, shows that, on average, the probability of being denied credit did not change over the 1980-2007 period, despite the extraordinary increase in US household debt.

as unconstrained if they hold positive amounts of net non-housing wealth.[24] Information on wealth holdings is available for 1984, 1989, 1994, 1999, and biennially thereafter, thus I estimate the probability of household having positive net non-housing wealth for the missing years.[25] Once households are classified into constrained and unconstrained, based on the actual and estimated probability of having positive non-housing net wealth,[26] I split the sample and estimate equation (5) on the sample of unconstrained households.[27]

This split might be too restrictive as I might be counting as constrained those households that were actually unconstrained, since households with zero net worth might still be able to borrow. Since information on availability of credit and ability of households to receive a loan of desirable size is unavailable in PSID, it is difficult to know how many households I am under/over classifying. Combining Survey of Consumer Finances, which provides such information but is not a panel and does not have information on consumption, and PSID data, Jappelli et al. [1998] find that only 12 percent of households classified as liquidity constrained based on having positive assets (not positive net wealth) are actually unconstrained, whereas 5 percent of households that are classified as unconstrained are actually liquidity constrained.[28] Even though Jappelli et al. [1998] results do not fully eliminate the

[24]Net worth was calculated as the sum of the net values of the following assets owned by the households: real estate other than main home, vehicles, farms or businesses, private annuities, IRAs, money in checking or savings accounts, money market funds, certificates of deposit, government saving bonds, Treasury bills, and any other savings or assets; minus any other debts held by a household.

[25]For each year wealth data is available, I estimate probability of having positive net non-housing wealth, as a function of observable characteristics such as age, age squared, cohort, race, gender, education, real house value, real rental and mortgage cost, dummy for whether renter or owner, marital status, number of kids, number of adults, real family income, real asset income, information on welfare, unemployment or other public transfers receipts, and state of residence. I estimate these probit regressions for available year of data, and predict the expected probability of having positive non-housing net wealth for previous 5 years.

[26]Household is classified as unconstrained if it has positive non-housing wealth for the years wealth data is available, or if the data is not available, based on the estimated probability of having positive non-housing net wealth being greater than 0.5.

[27]This strategy is very similar to the one employed by Zeldes [1989] or more recently by Parker and Preston [2005].

[28]Jappelli et al. [1998] find that households with less than college education, unemployed, or younger than

danger of misclassification, it seems that losing unconstrained households, and misclassifying constrained households, should lower the power of estimated coefficients, but it should not bias the results. In one of the model specifications I will control for this misclassification by including the estimated probability of having positive non-housing net wealth as one of the regressors.

The precautionary saving motive depends on the household's expectations about the uncertainty associated with future exogenous variables, such as for example, uncertainty about income and/or health. Families with higher uncertainty of future family income will have higher savings and therefore lower consumption today. Some families might have higher uncertainty of medical expenses and thus lower consumption. As pointed out by Browning and Lusardi [1996], precautionary savings also depend on the current level of cash-on-hand relative to expected future income. Families with identical income volatilities but lower current wealth will have higher precautionary savings. I proxy precautionary savings using the estimated volatility of family income, $\sigma^2_{h,a,t}$, computed according to equation (2). To control for cash-on-hand, I include as regressors information on the change in the value of real rental payments and real mortgage payments, the change in whether household owns or rents, and the change in the value of their house.

Food consumption is measured as a sum of food at home plus food away from home plus food stamps. As households grow richer, they substitute basic food items for those of higher quality (and thus more expensive goods) or into food away from home. Before the 1970s, food away from home constituted a very small proportion of annual food expense. But, since then, while food prices fell dramatically,[29] the number of fast food restaurants per capita doubled and the number of full-service restaurants per capita increased by 35%,[30] and food away from home took a larger proportion of household's expenditure. In addition,

38 are more likely to be turned down for a loan. Lyons [2003] finds that borrowing gap has narrowed since 1983 and most dramatically between 1992 and 1998. But that individuals younger than 35, who are black, or poorly educated continued to be constrained, though the constraints have loosened for them as well.

[29]See Figure A1 in the Appendix.

[30]See for example Cutler et al. [2003], or Chou et al. [2004] for detailed review of food prices and evolution of restaurants.

due to rising working hours and female labor force participation, preparation cost for food at home increased. Thus, I find it more appropriate to use the total food bill as a measure of household consumption.

3.1 Estimation Strategy

The estimation strategy allows for household fixed effects to account for household specific discount factors. I also control for the possibility that labor decisions are not separable from the marginal utility of consumption by including the change in the total number of hours worked by the head of the household and by their partner.[31]

To address endogeneity that arises due to presence of second and higher-order terms in the residual, it is typical to estimate the model using as instruments information known at time t.[32] Since the instrument set includes lagged terms of all the parameters in the Euler equation, it violates strict exogeneity assumptions required by the IV estimator. Additionally, as pointed out by Nickell [1981] estimated coefficients under within estimator together with predetermined regressors will give biased and inconsistent results.[33] One more issue to keep in mind is the limited temporal size of this highly unbalanced sample.

To get consistent estimates, I use forward orthogonal deviations transform in order to purge the data from fixed effects proposed by Arellano and Bover [1995]. I use orthogonal transformation instead of first differences, as forward transform reduces the loss of observations when the data is highly unbalanced. Instead of subtracting the previous observation from the contemporaneous one, forward transform subtracts the average of all future available observations of a variable. Thus it minimizes data loss, and since lagged observations don't enter the formula, they become valid instruments. I perform a two-step Arellano-Bond (AB) GMM estimation that allows for heteroscedasticity and intragroup correlation. I also make the Windmeijer finite-sample correction to the reported standard errors in two-step

[31]The inclusion of the information on the labor supply decision is important for the identification purposes, see Attanasio [1999].

[32]See Attanasio and Low [2004] for a detailed discussion of issues involved in estimating Euler equations.

[33]I thank the anonymous referee for this comment.

estimation, without which those standard errors tend to be severely downward biased. I limit the number of instruments to one lag, and use second lag of the explanatory variables plus marginal tax rate as instruments, in order to reduce the potential efficiency loss this type of GMM estimators could suffer. Too many instruments will not compromise the coefficient estimates but will weaken the Sargan/Hansen test of overidentifying restrictions. In addition, too many instruments can over-fit endogenous variables.[34]

In my preferred estimation, I control for both nonseparabilities of preferences, liquidity constraints, and the estimated probability of having positive net-wealth. By including the estimated probability of having positive wealth, I control for the possibility of misclassification of households into liquidity constrained and unconstrained. All the necessary tests for the consistency of estimation are passed. Specifically, I fail to reject the null for both the Sargan test (p-value=0.693) and the Hansen test (p-value=0.266) of overidentification restrictions.[35] My estimate of intertemporal elasticity of substitution (IES) is consistent with other studies and is estimated at 1.32 with robust standard error of 0.78.[36]

3.2 Evolution of Consumption Risk

To compute volatility of household consumption, I first predict residuals, $\widehat{z_{h,t+1}}$, from the Euler equation (5). I then subtract out household fixed effects κ_h, thus subtracting out household specific discount factors that are not directly computed by AB-GMM estimator, and time fixed effects τ_t, to center the residuals. I then construct consumption volatility parameter as the square of the residual $\widehat{\varsigma^2_{h,t+1}} = \left(\widehat{z_{h,t+1}} - \kappa_h - \tau_t\right)^2$.

To summarize the evolution of volatility of household consumption, I postulate that it is a function of a linear time trend and other explanatory variables, $X_{h,t}$:

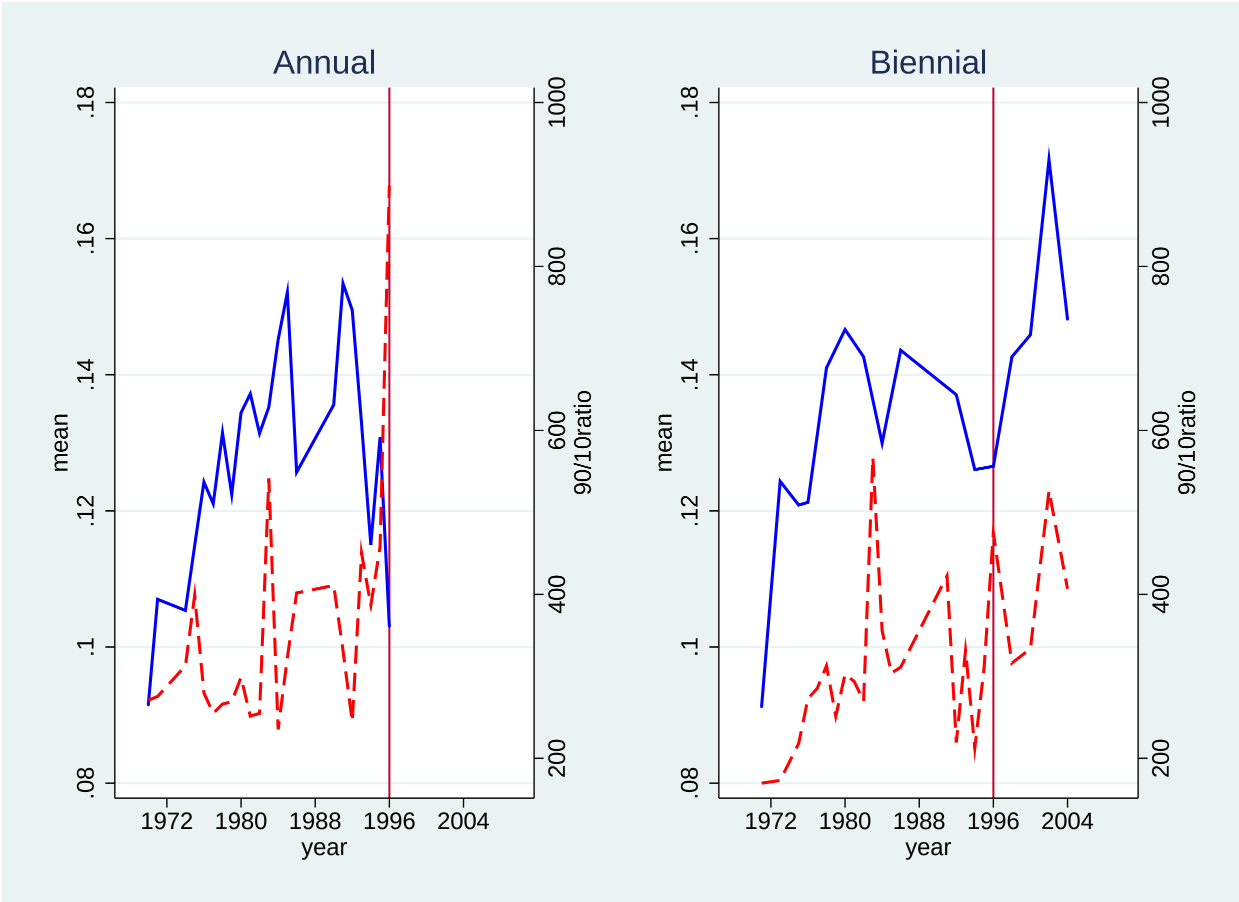
$$\widehat{\varsigma^2_{h,t+1}} = \beta_{0,g} + \beta_{1,g} t + X'_{h,t}\gamma_g + \omega_{h,t+1} \tag{6}$$

[34]See for example Roodman [2009] on the problems too many instruments could cause this type of GMM estimator.

[35]In Tables 3 and 4 in the Appendix provide detailed estimates of the Euler equation using simple OLS, LSDV and GMM estimation strategies.

[36]See for example Attanasio and Weber [1995], Attanasio [1999], and Attanasio and Low [2004].

Figure 2: Volatility of Food Consumption



Legend Key: Long-dash is for 90/10 percentile ratio, and solid is for the average of volatility of food consumption.

Note: Annual graph is based on annual growth rates data sample, and biennial graph on the biennial growth rates sample computed using even years of data only.

where $\beta_{0,g}$ reflects the variance of the measurement error, which is assumed to be stationary and household (or group) specific.

Figure 2 provides graphical illustration of the mean and the 90/10 percentile ratio of volatility of food consumption for annual and biennial data samples.[37] The graph illustrates

[37]To compute food volatility on the biennial sample, I run the Euler equation on the biennial growth rates, or $ln(F_{h,t}) - ln(F_{h,t-2})$, I then compute volatility as a squared residual from this Euler equation, after

that food consumption volatility increased by 60 percent between 1968 and 1985, stayed high until early nineties, fell 30 percent between 1993 and 1996, and then increased significantly until 2002, rising by 36 percent. Overall, between 1986 and 2004, the average household experienced an increase of 68 percent in household food consumption. The 90/10 percentile ratio, though highly variable, also exhibited a positive and significant trend over the period, more than doubling between 1968 and 2004. The reason for this trend comes from the fact that 90th percentile increased steadily, whereas 10th percentile exhibited a downward trend over the entire period.

Table 1 summarizes regression results on annual and biennial sample for volatility of food and volatility of family income for an average household, and illustrates some very interesting differences. The increase in volatility of family income was significantly larger than that of food expenditure: whereas volatility of family income doubled over the entire period, that of food expenditure rose by 43 percent (based on trend calculations). The differences are particularly stark for the 1970 to 1996 period: volatility of income increased by 70 percent and that of food by 17 percent between 1970 and 1996; on the other hand, volatility of income went up by 25 percent and that of food by 19 percent between 1996 and 2004.

Table 1: Volatility of real family income and real food expenditure, annual and biennial samples.

	annual		biennial		biennial, year> 1995	
	food	income	food	income	food	income
year/1000	0.79***	3.58***	0.96***	3.44***	3.19***	6.09***
	(0.18)	(0.27)	(0.16)	(0.24)	(1.10)	(1.84)
Constant	-1.43***	-6.96***	-1.77***	-6.66***	-6.24***	-11.96***
	(0.36)	(0.53)	(0.31)	(0.47)	(2.20)	(3.69)
Observations	37,696	37,696	39,425	39,425	9,757	9,757
R-squared	0.00	0.01	0.00	0.01	0.00	0.00

Robust standard errors in parenthesis: *** $p < 0.001$, ** $p < 0.05$, * $p < 0.1$

Not all households were affected equally by these trends in income volatility. Table 2

removing first the household fixed effects, to remove household specific discount factors, and time dummies, to center the results.

illustrates these differences on the biennial sample of data.[38] The base group for these regressions is a head of the household who is white, has more than 12 years of education, is not a single parent and whose family income belongs to the median of the income distribution. Education played an important role in the way households were affected by income shocks. Income volatility increased by less for households with less than 13 years of education than for those with more education over 1970 to 2004 period. On the other hand, food consumption volatility rose by significantly more for households with low education. These trends remained even after other controls were added to the regressions. Thus, households with a high school degree or less had a harder time smoothing income shocks that were, at the same time, not as high as those experienced by more educated households.

Volatility of family income had a similar increase for white and nonwhite households, but nonwhite households were unable to smooth consumption in the same way as white households. Volatility of food consumption increased by 52 percent for the nonwhite households, whereas white households experienced a much lower, though still high, 25 percent increase. Having higher education did not seem to help nonwhite households either.[39] On the other hand, white households with less than 13 years of education endured a higher trend in consumption volatility than whites with higher education, though the increase for these households was still not as high as that for nonwhite households.

Since nonwhite and poorly educated households are typically those with lower family income, controlling for income and the position of household within income distribution might eliminate these differences. Table 2 illustrates that race and education continue to play a significant role even after income, working history, income quintiles, education, marital status, size of the household, and age, were controlled for. It is in fact true that households with higher family income had lower levels of both volatility of income and consumption. Nevertheless, volatility of food consumption increased considerably for these households, whereas income volatility increased by less (for poorly educated) or by the same amount (for

[38]Results for the annual sample are comparable and are available upon request.

[39]This observation might be a result of a very small sample of nonwhite households with more than 12 years of education.

nonwhite) as for the whites with higher education.

Did the magnitude of the shock play an important role in the way volatility of income translated into volatility of consumption? Figures 1 and 2 gave a preview to the fact that there were significant difference in the way 90th and 10th percentiles of the shock distribution behaved from that of the mean. Table 3 reports regression results for simultaneous-quantile regressions for 0.10, 0.50 and 0.90 quantile of volatility of income and of volatility of food expenditure on biennial sample.[40] Major increase in volatility came from the increase in the 90th percentile of the volatility distribution, i.e. large shocks to income and to consumption increased significantly over the 1970-2004 period. There was an increase in median sized shocks as well, though this increase was significantly lower than that of the 90th percentile of the distribution.

There are also some very interesting differences on how income shocks behaved depending on where within the income distribution households' family income lay. In particular, the rise in income volatility was largest for the lowest quintile of the income distribution, even after controlling for movements between quintiles. Similarly, households who were in the top quintile experienced a high increase in income volatility, though for these households, the increase was significantly lower than that for the bottom of the income distribution. Combining these observations with the simultaneous quantile regressions, we see that indeed, households in the lowest quintile of the income distribution experienced a 200 percent increase in volatility of income, if they also belonged to the 90th percentile of the income volatility distribution; that compared to a 74 percent increase for the median family, and a 146 percent increase if the household belonged to the top 20 percent of the income distribution. In contrast, income quantiles did not play an important role in the way food volatility evolved over time across different quintiles of the shock distribution. What seemed to matter most again was race and education of the head of the household, and not in the income distribution where they belonged.

Unlike mean regressions, quantile regressions show some differences in income shocks af-

[40] Estimates on annual data are similar and are available upon request.

fecting nonwhite households. In particular, income volatility increased for nonwhite households that belonged to the bottom 10 percent and the median of the income shock distribution. Volatility of food consumption, on the other hand, increased for the nonwhite households across volatility distribution significantly more than for the white households, especially for those nonwhite households who belonged to the 90th percentile of the shock distribution. Thus, even though evolution of large income shocks was not different for white and nonwhite households, ability of nonwhite households to smooth out these shocks was much smaller than that of white households. Education also played an important role. Large shocks to income increased by significantly less for poorly educated households than for well educated. Nevertheless, these shocks were high enough to guarantee that poorly educated households were unable to smooth them in the same way as well educated households. Thus, volatility of food consumption for households with less than 13 years of education increased by more than for those with more education, especially if these households belonged to the 90th percentile of the shock distribution.

3.3 Why were nonwhite and poorly educated less able to smooth income shocks?

To summarize, I find that even though higher income and higher education households experienced greater increase in income uncertainty, traditionally vulnerable households (those with low education, lower income, and/or who were nonwhite) experienced a disproportionately higher increase in food consumption volatility. Not all income shocks were translated into volatility of food expenditure, or households were able to smooth out a large fraction of income shocks. Nevertheless, an increase in volatility of food expenditure, indicates that household welfare was negatively affected by increased income uncertainty, and welfare of nonwhite and poorly educated was affected the most.

Could the difference between the ability of white and nonwhite households to weather increasing income shocks be due to lifestyle choice of these households? Are white and nonwhite households spending their money on different types of foods that have inheritably different volatility properties? I investigate this question by adding a new variable into the regression: share of food at home in the total food bill. While this variable is statistically significant, and shows that the increase in food volatility comes primarily from volatility in the food away from home, it again does not eliminate the racial divide. Even controlling for the share of the food bill spent on food at home, nonwhite households experience a much more significant increase in volatility of food consumption than white households with the same food at home share.

Is it possible that public transfers favored white households? Nonwhite households in the sample were more likely to receive public transfers than white households, 25 vs. 14 percent in 2004, respectively; and received on average higher transfers, $275 more than white, who received $547 in 2004. In fact, recent work by Moffitt and Scholz [2009] finds that there was a redistribution of income from the very poor to near-poor and non-poor households, as the later group experienced an increase in benefits over 1984 to 2004 time period. However, even though public transfers reduced the level of volatility experienced by its recipients, they were not enough to reduce its growth.

Why were nonwhite and poorly educated households then unable to smooth out income shocks to the same extent as white and better educated households? Vulnerable households are typically households with low assets and significantly lower ability to access credit markets. Examining summary statistics by race, the racial divide is clear: white households have higher incomes, (white had $52,294 and nonwhite $34,520 in 2004), higher net wealth holdings (including or excluding housing wealth), and are much less likely to have less than 2 months worth of family income in liquid assets. Even though the gap between white and nonwhite households has fallen over the period, in 2004, one in 3 nonwhite unconstrained households had less than 2 months of income in savings, versus 2 in 5 in 1983, but only 1 in 5 white households were in the same position in 2004 (these differences are statistically significant at $p=0.000$).

Nonwhite and poorly educated households were also considerably more likely to be denied credit and this probability did not improve much over the period. Using the Survey of

Consumer Finances data Dogra [2009] estimates evolution of liquidity constraints between 1980 and 2004. Dogra counts a household as liquidity constrained if either it had a request for credit turned down and it was not able to obtain the full amount by reapplying or applying elsewhere, or if it was discouraged from applying because it though it would be turned down. He finds that poorer households, single parents and nonwhites, particularly those with 12 or less years of education, are still the most likely to be constrained, and that there is no evidence that liquidity constraints slackened for these groups over the 1980-2004 period. Gorbachev and Dogra [2009] continue this exercise by estimating liquidity constraints in PSID data extending Jappelli et al. [1998] work on how to combine PSID and SCF surveys to construct such measures. Their work shows that after 1995, credit constraints relaxed for better off households - those in the upper income quantiles, and those with more than 12 years of education. By contrast, for poorer households, and those with less education, the probability of being denied credit remained the same or even increased after 1998, and the percentage of such households without a credit card also increased. Gorbachev and Dogra [2009] also find that nonwhite and poorly educated households are much more likely to be denied credit than white and well educated households, and that this probability did not fall over the 1980-2004 period. This observation goes against the common wisdom that liquidity constraints relaxed since 1980s, and in particular against the view that vulnerable households are now more likely to obtain loans (the view propagated by the subprime mortgage crisis). While supply of credit increased dramatically over the period, as the mean real debt for all households increased by 170%, from $17,000 to $47,000 (in 1983 dollars), between 1983 and 2007, an increase in debt does not imply that more consumers can obtain as much as they desire. If, for example, consumers' demand for debt has increased in line with the supply of credit, the stock of consumer liabilities might increase, while the proportion of households unable to borrow as much as they desire remains the same, or increases.

Given these trends in liquidity constraints and liquid asset holdings, it is not surprising that nonwhite and poorly educated households were unable to smooth out increased income shocks to the extent white and well educated households did, and that the welfare cost from increased income uncertainty to these vulnerable households was significantly larger.

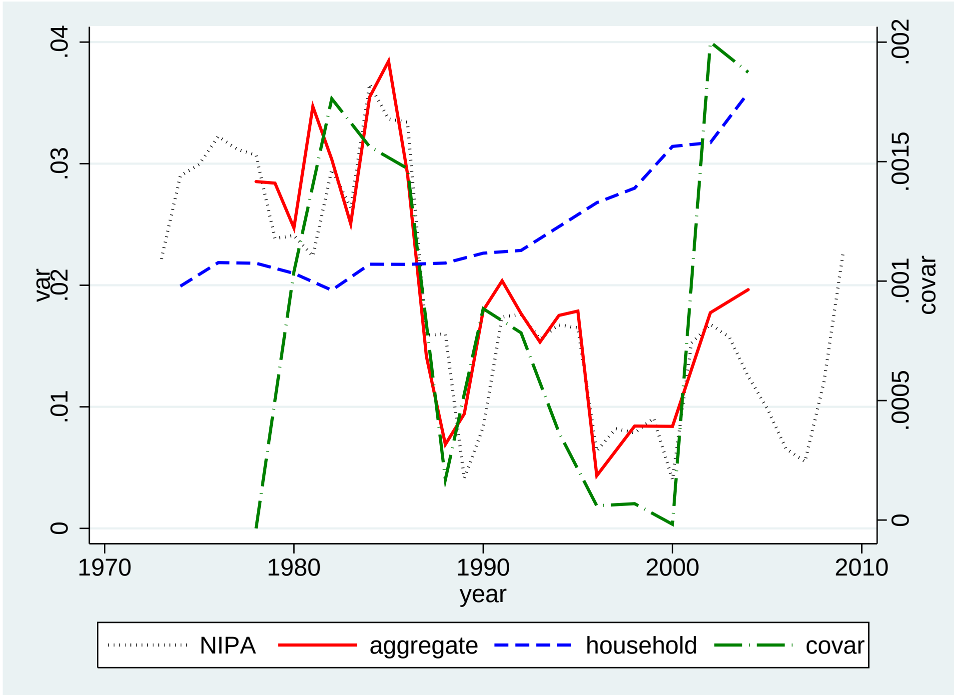
Since food consumption is well known to have low income elasticity, (see for example, Bunkers and Cochrane [1957]), the results presented here are a lower bound of what might have actually happened to volatility of total nondurable consumption. I follow Blundell et al. [2008] and estimate responsiveness of food consumption to changes in nondurables. Using data from Consumer Expenditure Survey for 1980-2004 period,[41] I estimate a demand equation for food as a function of relative prices, as well as nondurable expenditure and a host of demographic and socioeconomic characteristics of the household. Similar to Blundell et al. [2008], I find that the elasticity of food consumption with respect to nondurable consumption is 0.85 and is highly statistically significant (p=0.000). Even though this elasticity changes over time, I cannot reject the joint significance test, regressions don't have enough power to estimate precisely these changes. I also estimate demand equations for each year of available data, and find that the budget elasticity falls over time, though I cannot reject equality of the estimated coefficients. Elasticity is estimated at 0.69 (with standard error of 0.31) in 1980, 0.59 (s.e. 0.28) in 1990, and 0.56 (s.e. 0.21) in 2004. Keeping to conservative estimates (those obtained from the pooled regression model with controls for time changes in the elasticity parameter), a 1 percent change in nondurable consumption will lead to a 0.85 percent change in food expenditure. Therefore, a 1 percent increase in volatility of food consumption will translate into a $1.38 = 1/(0.85)^2$ percent increase in volatility of nondurable consumption; or a 43 percent increase in food consumption volatility translates into a 60 percent increase in volatility of nondurable consumption. If changes in the elasticity are taken into account this too is an underestimate.

4 Conclusion

The increase in household income and consumption risk over 1970-2004 stands in sharp contrast to the dramatic fall in aggregate volatility of the US economy over the 1984-2004 period. Aggregate volatility of the US economy fell by 60 percent since 1984. Volatility

[41] Blundell et al. [2008] study used data for 1980-1992 period only.

Figure 3: Aggregate vs. Household Income Volatility



Source: National Income and Public Accounts data and Panel Study of Income Dynamics.

Note: NIPA refers to volatility of GDP using NIPA data, all the other series are computed using PSID. Variance and covariances are computed on a 5-year moving window. Average household volatility series was scaled down by 10 in order to fit it onto the same graph with aggregate volatility and average covariances.

of aggregate real food consumption also fell over 1970-2004 period, dropping by 73 percent since its peak in 1976. Aggregate volatility computed on PSID data tracks remarkably well volatility computed on NIPA data. After 2000, aggregate volatility in PSID shows a stronger rise than that observed in NIPA. Nevertheless, correlation of the two series is 0.86 for years before 1996 and 0.9 after 1995.

From a simple decomposition, it is easy to see how the current situation, in which aggregate volatility fell but mean household volatility increased, might occur. Assuming for simplicity that aggregate consumption growth, γ_t^C, can be expressed as an average of household consumption growth rates, $\gamma_{h,t}^c$, then aggregate volatility, $Var_t\left[\frac{1}{H}\sum_{h=1}^{H}\gamma_{h,t}^c\right]$, can be decomposed into average household volatility, $\frac{1}{H^2}\sum_{h=1}^{H}Var_{h,t}(\gamma_{h,t}^c)$, plus average covariances between different households, $\frac{2}{H^2}\sum_{i \neq j} Cov_t(\gamma^c_{i,t}, \gamma^c_{j,t})$. Thus, aggregate volatility could go down while average household volatility goes up, if average covariances fall enough to compensate for this differential.

Figure 3 illustrates this concept on PSID and NIPA data. To be consistent with the way aggregate volatility is computed in the macro literature,[42] I calculate volatility (and covariances) as a 5-year moving variance (covariance) on demeaned family income growth, and not on the idiosyncratic shocks to income. The graph illustrates that in the US economy, between 1984 and 2000, aggregate shocks became less important as a source of variation of household income. It also illustrates that average covariances follow closely the trend in aggregate volatility, though on a very different scale. The data covers two major recessions in the US, that of 1980-1982 and 2001. During these recessions, there was a rise in both average covariances and aggregate volatility series.[43] The rise in average covariances is, in percentage terms, quite dramatic. Even though my data does not cover the current recession, it is likely that both household income volatility and average covariances continued to rise after it's unset. As the period of relative economic stability, 1984 to 2000, illustrates: low aggregate uncertainty is not a guarantee that household income risk will also be low. On the other hand, a deep recession reinforces idiosyncratic shocks making an already bad situation worse.

There have been several significant changes in patterns of volatility in the US economy over the past several decades. Income volatility, and both its transitory and permanent components increased since 1970, leading to a significant rise in consumption volatility. Possible explanations for these trends might include greater wage flexibility,[44] fall in progressivity of

[42]See for example McConnell and Perez-Quiros [2000], Stock and Watson [2002], and Blanchard and Simon [2001].

[43]Recessions are (almost by definition) a time of large, negative, aggregate shocks to household income. Correlation coefficients will depend on the variance of aggregate shocks relative to the variance of idiosyncratic shocks. So correlation will go up in a recession, because idiosyncratic shocks are the same as usual and aggregate shocks are much larger.

[44]Davis and Kahn [2008] put forward this explanation in their recent survey of evolution of volatility in macro and micro data.

the US tax code,[45] changes in the generosity of the welfare programs especially after the reforms of 1996,[46] and increases in health care costs. For nonwhite households and those with low education the ability to smooth income shocks was particularly hampered by low holdings of net wealth and poor access to credit markets.

[45] According to Piketty and Saez [2007] the U.S. tax system became less progressive over the last 40 years. There have also been important changes to capital taxation. For example, Dai et al. [2008] analyze the effect that the Taxpayer Relief Act of 1997 had on increase in stock return volatility. This increase, they point out, is due to the reduced risk sharing between the investors and the government, which increased consumption risk.

[46] See work by Moffitt and Scholz [2009] for a recent review of the evolution of welfare program in the US over the last 30 years.

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Table 2: Volatilty of food or income by race of the head of the household , biennial sample

	all		food		income		year>1977		food, year>1977	
VARIABLES	food	income	white	nonwhite	white	nonwhite	food	income	white	nonwhite
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
year/1000	1.556***	4.566***	1.379***	4.683**	4.458***	5.554***	5.054***	5.371***	5.168***	5.965
	(0.392)	(0.516)	(0.398)	(1.976)	(0.529)	(1.743)	(1.692)	(1.623)	(1.743)	(7.105)
nonwhite * year/1000	0.819	0.080					1.448*	0.078		
	(0.652)	(0.816)					(0.858)	(1.101)		
single parent * year/1000	0.888	-0.019	1.111	0.787	0.419	0.177	0.502	-1.040	1.287	-2.064
	(0.924)	(1.310)	(1.012)	(2.198)	(1.496)	(3.108)	(1.308)	(1.769)	(1.458)	(2.766)
edu<13 * year/1000	0.594*	-2.352***	0.621*	0.085	-2.507***	0.587	-0.236	-2.508***	-0.274	-0.407
	(0.359)	(0.558)	(0.368)	(1.539)	(0.584)	(1.765)	(0.467)	(0.700)	(0.482)	(1.854)
food at home as share of total food * year/1000							-4.854**	-1.265	-5.235**	-1.086
							(2.075)	(1.951)	(2.147)	(7.960)
food at home as share of total food							9.502**	2.419	10.255**	1.999
							(4.129)	(3.882)	(4.270)	(15.884)
ln(real family income)	-0.015**	-0.163***	-0.015**	-0.009	-0.142***	-0.431***	-0.014**	-0.159***	-0.017**	0.014
	(0.006)	(0.028)	(0.007)	(0.025)	(0.028)	(0.083)	(0.007)	(0.030)	(0.007)	(0.021)
ln(real public transfers)	0.004***	0.006***	0.004***	-0.001	0.006***	0.006**	0.003***	0.006***	0.004***	-0.004*
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
1st income quintile * year/1000	-1.990***	7.514***	-1.976***	-2.910	8.203***	0.007	-3.093***	9.677***	-3.276***	-2.839
	(0.695)	(1.320)	(0.731)	(2.477)	(1.466)	(2.727)	(0.931)	(1.739)	(0.986)	(3.185)
2nd income quintile * year/1000	-1.323**	0.881	-0.979*	-4.824**	1.166*	-2.504	-1.448**	0.921	-1.218*	-4.048
	(0.523)	(0.639)	(0.538)	(2.127)	(0.683)	(1.708)	(0.670)	(0.852)	(0.695)	(2.643)
4th income quintile * year/1000	-0.837*	-0.774	-0.597	-3.845*	-0.871*	0.184	-1.150*	-0.856	-0.869	-4.993*
	(0.454)	(0.489)	(0.463)	(2.057)	(0.507)	(1.792)	(0.597)	(0.635)	(0.610)	(2.692)
5th income quintile * year/1000	-0.253	1.946***	-0.046	-2.313	1.635**	5.943**	-0.331	2.671***	0.035	-6.328*
	(0.469)	(0.640)	(0.476)	(2.319)	(0.659)	(2.468)	(0.608)	(0.809)	(0.614)	(3.266)
change in number of hours worked, head	-0.002	-0.018**	-0.003	-0.000	-0.014**	-0.042*	-0.000	-0.017**	-0.000	0.000
	(0.004)	(0.007)	(0.004)	(0.008)	(0.007)	(0.025)	(0.004)	(0.008)	(0.004)	(0.006)
number of hours worked, head	0.000**	0.000***	0.000**	-0.000	0.000***	0.000	0.000	0.000***	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
change in number of hours worked, wife	-0.000	0.001	-0.000	0.001	0.001	-0.003	0.000	0.000	-0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.004)	(0.001)	(0.001)	(0.001)	(0.003)
Age	0.004**	-0.002	0.004***	-0.004	-0.001	-0.012	0.003	-0.000	0.004**	-0.011*
	(0.002)	(0.002)	(0.002)	(0.006)	(0.002)	(0.008)	(0.002)	(0.003)	(0.002)	(0.006)
Age squared	-0.000***	0.000	-0.000***	0.000	0.000	0.000	-0.000	0.000	-0.000**	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
nonwhite	-1.603	-0.184					-2.859*	-0.180		
	(1.296)	(1.618)					(1.706)	(2.188)		
single parent	-1.792	-0.010	-2.232	-1.594	-0.875	-0.425	-1.014	2.028	-2.574	4.096
	(1.838)	(2.599)	(2.012)	(4.372)	(2.967)	(6.180)	(2.605)	(3.517)	(2.904)	(5.507)
education<13	-1.185*	4.654***	-1.239*	-0.185	4.960***	-1.168	0.469	4.965***	0.547	0.797
	(0.714)	(1.107)	(0.731)	(3.061)	(1.159)	(3.504)	(0.928)	(1.390)	(0.959)	(3.690)
change in marital status	0.072***	0.140***	0.073***	0.062*	0.149***	0.064*	0.066***	0.139***	0.069***	0.043
	(0.009)	(0.012)	(0.009)	(0.035)	(0.012)	(0.035)	(0.010)	(0.013)	(0.010)	(0.037)
change in number of adults	0.004	-0.010**	0.003	0.014	-0.013**	0.004	0.004	-0.010*	0.003	0.000
	(0.004)	(0.005)	(0.004)	(0.015)	(0.005)	(0.014)	(0.004)	(0.006)	(0.004)	(0.017)
number of adults	-0.013***	0.017***	-0.013***	-0.009	0.020***	-0.000	-0.004	0.022***	-0.003	-0.000
	(0.003)	(0.004)	(0.003)	(0.012)	(0.004)	(0.010)	(0.004)	(0.005)	(0.004)	(0.015)
change in number of kids	-0.011***	0.001	-0.001	-0.004	-0.006	-0.006	-0.003*	0.005*	0.000	-0.026
	(0.001)	(0.002)	(0.003)	(0.016)	(0.004)	(0.011)	(0.002)	(0.002)	(0.004)	(0.016)
number of kids	-0.001	-0.006	-0.011***	-0.010**	0.000	0.001	-0.002	-0.005	-0.003*	-0.003
	(0.003)	(0.004)	(0.001)	(0.005)	(0.002)	(0.006)	(0.004)	(0.005)	(0.002)	(0.006)
1st income quintile	4.017***	-14.820***	3.995***	5.819	-16.148***	-0.289	6.218***	-19.126***	6.585***	5.711
	(1.379)	(2.621)	(1.452)	(4.912)	(2.910)	(5.399)	(1.852)	(3.457)	(1.962)	(6.331)
2nd income quintile	2.638**	-1.764	1.955*	9.577**	-2.322*	4.858	2.888**	-1.841	2.431*	8.046
	(1.038)	(1.267)	(1.069)	(4.222)	(1.354)	(3.383)	(1.333)	(1.692)	(1.383)	(5.253)
4th income quintile	1.661*	1.573	1.187	7.594*	1.762*	-0.257	2.280*	1.734	1.725	9.872*
	(0.901)	(0.969)	(0.919)	(4.083)	(1.005)	(3.549)	(1.188)	(1.262)	(1.213)	(5.352)
5th income quintile	0.512	-3.701***	0.101	4.607	-3.097**	-11.480**	0.655	-5.157***	-0.071	12.583*
	(0.930)	(1.263)	(0.945)	(4.599)	(1.301)	(4.877)	(1.209)	(1.600)	(1.221)	(6.498)
change in quintile	0.007***	-0.022***	0.007***	0.017	-0.023***	-0.011	0.008***	-0.024***	0.007***	0.022*
	(0.002)	(0.006)	(0.002)	(0.010)	(0.006)	(0.018)	(0.002)	(0.007)	(0.002)	(0.012)
Constant	-2.857***	-7.315***	-2.521***	-8.920**	-7.354***	-6.163*	-9.716***	-8.931***	-9.950***	-11.497
	(0.777)	(0.966)	(0.790)	(3.905)	(0.991)	(3.373)	(3.358)	(3.222)	(3.457)	(14.154)
Observations	37526	37526	34492	3034	34492	3034	31181	31181	28710	2471
R-squared	0.022	0.079	0.022	0.023	0.078	0.148	0.029	0.080	0.030	0.034

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Information on food at home as a share of total food expenditure is available from 1978 onwards due to availability of relevant CPI data.

Table 3. Quantile regressions: volatility of food expenditure vs. volatility of family income, biennial sample

	food			income			food			income		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	q10	q50	q90	q10	q50	q90	q10	q50	q90	q10	q50	q90
year/1000	-0.014***	0.402***	4.877***	-0.001	0.266***	5.398***	-0.019***	0.167	2.528***	-0.004	0.290***	7.562***
	(0.004)	(0.146)	(1.199)	(0.005)	(0.092)	(0.949)	(0.005)	(0.154)	(0.939)	(0.004)	(0.062)	(0.840)
nonwhite * year/1000							-0.001	0.758**	4.028**	0.025*	0.221*	1.024
							(0.011)	(0.315)	(1.653)	(0.015)	(0.129)	(1.864)
nonwhite							0.003	-1.492**	-7.940**	-0.049*	-0.436*	-2.055
							(0.022)	(0.625)	(3.273)	(0.029)	(0.256)	(3.695)
single parent * year/1000							0.006	0.381	2.247	0.043	0.564	3.225
							(0.012)	(0.471)	(4.249)	(0.030)	(0.367)	(4.232)
single parent							-0.012	-0.758	-4.479	-0.086	-1.122	-6.413
							(0.024)	(0.934)	(8.417)	(0.060)	(0.729)	(8.381)
edu<13 * year/1000							0.012**	0.383***	2.725***	0.008	-0.053	-4.198***
							(0.006)	(0.124)	(0.914)	(0.006)	(0.090)	(0.979)
edu<13							-0.023**	-0.765***	-5.445***	-0.016	0.107	8.319***
							(0.011)	(0.245)	(1.815)	(0.012)	(0.178)	(1.942)
1st income quintile * year/1000	-0.010	0.113	-2.319	0.056***	2.115***	29.175***	-0.016*	-0.152	-2.710	0.044**	2.069***	28.765***
	(0.012)	(0.364)	(2.355)	(0.021)	(0.451)	(3.927)	(0.008)	(0.332)	(2.571)	(0.018)	(0.545)	(5.557)
2nd income quintile * year/1000	0.004	-0.064	-1.405	-0.010	-0.090	5.060**	0.002	-0.147	-1.037	-0.018*	-0.119	5.246***
	(0.005)	(0.175)	(1.465)	(0.009)	(0.164)	(2.061)	(0.007)	(0.217)	(1.751)	(0.010)	(0.165)	(1.977)
4th income quintile * year/1000	0.004	-0.102	-2.328*	-0.003	-0.190	-2.183*	0.003	-0.082	-1.740	-0.004	-0.203**	-2.867**
	(0.005)	(0.187)	(1.377)	(0.009)	(0.118)	(1.319)	(0.006)	(0.146)	(1.076)	(0.006)	(0.081)	(1.185)
5th income quintile * year/1000	0.009	0.018	-2.153	0.018**	0.130	5.023***	0.008	0.064	-0.712	0.019***	0.121	3.603**
	(0.008)	(0.179)	(1.649)	(0.007)	(0.125)	(1.366)	(0.010)	(0.164)	(0.918)	(0.007)	(0.131)	(1.461)
1st income quintile	0.021	-0.200	4.872	-0.110***	-4.141***	-57.140***	0.032*	0.326	5.652	-0.087**	-4.049***	-56.327***
	(0.023)	(0.722)	(4.682)	(0.041)	(0.896)	(7.771)	(0.016)	(0.659)	(5.094)	(0.035)	(1.080)	(11.009)
4th income quintile	-0.009	0.131	2.840	0.020	0.191	-9.923**	-0.004	0.296	2.107	0.036*	0.249	-10.286***
	(0.011)	(0.347)	(2.911)	(0.017)	(0.326)	(4.083)	(0.013)	(0.430)	(3.472)	(0.019)	(0.327)	(3.915)
2nd income quintile	-0.007	0.202	4.608*	0.005	0.374	4.289	-0.007	0.161	3.440	0.007	0.402**	5.637**
	(0.009)	(0.373)	(2.738)	(0.018)	(0.235)	(2.613)	(0.011)	(0.291)	(2.136)	(0.012)	(0.161)	(2.348)
5th income quintile	-0.018	-0.035	4.262	-0.035**	-0.251	-9.905***	-0.016	-0.128	1.396	-0.038***	-0.233	-7.093**
	(0.016)	(0.356)	(3.276)	(0.015)	(0.249)	(2.706)	(0.021)	(0.326)	(1.819)	(0.013)	(0.260)	(2.892)
change in quintile	-0.000	0.002***	0.022***	0.000***	0.005***	0.027***	0.000	0.002***	0.021***	0.000***	0.005***	0.029***
	(0.000)	(0.001)	(0.004)	(0.000)	(0.001)	(0.003)	(0.000)	(0.001)	(0.005)	(0.000)	(0.001)	(0.004)
Constant	0.028***	-0.762***	-9.382***	0.002	-0.504***	-10.424***	0.039***	-0.294	-4.706**	0.008	-0.553***	-14.710***
	(0.008)	(0.289)	(2.384)	(0.009)	(0.184)	(1.881)	(0.011)	(0.306)	(1.863)	(0.008)	(0.123)	(1.665)
Observations	37787	37787	37787	37787	37787	37787	37529	37529	37529	37529	37529	37529

Boot strapped standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix to
"Did Household Consumption Become More Volatile?"

May 13, 2010

A Data Sample: Panel Study of Income Dynamics

The Panel Study of Income Dynamics (PSID), which began in 1968, is a longitudinal study of a representative sample of U.S. individuals (men, women, and children) and the family units in which they reside, and is conducted by the University of Michigan. The PSID's sample size has grown from 4,800 families in 1968 to more than 7,000 families (and over 60,000 individuals) in 2001. Some families are followed for as much as 36 consecutive years.

Consumption data in PSID are limited to food and shelter. I compute all the consumption volatility measures on food consumption calculated as a sum of food consumed at home plus away from home plus food stamps received. The core sample contains data from 1968 to 2005, and consists of heads of households (both female and male) who are not students and are not retired. I keep households whose head is at least 25 years old but less than 65. I drop all the households that belonged to the Latino or Immigrant samples, and those that were drawn from the Survey of Economic Opportunity (SEO). Households that report negative or zero total food consumption levels are also eliminated. In order to minimize effects of outliers on the results, I follow the literature by dropping households who report more than 500 percent change in family income or food consumption over a one year period as well as those whose income or consumption fall by more than 95 percent (see for example Zeldes [1989] or Blundell et al. [2008]).

The most important issue to note regarding the data is that it became biennial after 1997. Thus, I compute all my results on annual data before 1997. I then construct a hypothetical biennial sample to study the evolution of consumption volatility up to 2004. Since income and consumption data is collected for previous year, the biennial sample has data for *even* years from 1976 to 2004. In addition, food consumption data was not collected in 1973, 1988 and 1989. I do not impute for the missing years in order to keep measurement error and misidentification to a minimum.

At the time of the interview, the respondent is asked questions about income, transfers, wealth and expenditures on food and shelter. The families are asked to report income and transfers received during the previous year. I use total family income to compute income uncertainty. I adjust income data by one period to correspond to the appropriate demographic characteristics for each household. The timing of consumption data is more ambiguous. I follow Blundell et al. [2008], among many others, and assume that the respondent provided information on food expenditures for the previous year. I use an annual average of monthly data on 1-year constant maturity Treasury bills.

All the income, expenditure, wealth, and interest rate data are expressed in real terms. Nominal data are converted into real using item specific regional not seasonally adjusted all urban Consumers Consumer Price Index (CPI-U) with base period of 1982-1984=100. Thus, food expenditures are deflated using the Food and Beverages CPI; housing expenditures, using the Housing CPI; and all income, wealth and interest rate series, using All-Items CPI.

We separate our sample into liquidity constrained and unconstrained households using information from Wealth Supplements. Wealth information was collected in 1984, 1989, 1994, 1999 and biennially after that. Household is counted as liquidity unconstrained if they had positive non-housing net wealth. For the years when wealth data is unavailable, I estimate the probit regression, probability of having positive net non-housing wealth, as a function of explanatory variables.

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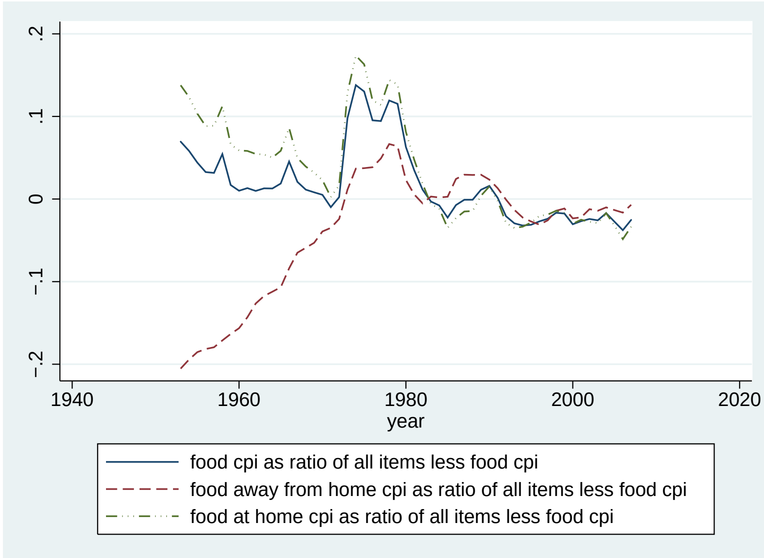
A.1 Supplementary Figures

Figure 1: The Ratio of Food Prices to the Price of All Other Goods, (1982-1984==100)



Source: Bureau of Labor Statistics.

A.2 Supplementary Tables

A1. Summary Statistics, households with positive net non housing wealth, or liquidity unconstrained households

	1970		1980		1990		2000		2004	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
age	41.93	11.35	38.36	10.45	39.20	8.79	42.57	9.72	43.06	10.77
number of adults	2.08	0.71	1.96	0.67	1.94	0.64	1.98	0.71	1.94	0.67
number of kids	1.47	1.46	1.17	1.19	1.10	1.17	0.92	1.11	0.86	1.07
female	0.13	0.33	0.14	0.34	0.14	0.35	0.16	0.36	0.17	0.37
nonwhite	0.10	0.30	0.09	0.29	0.09	0.29	0.10	0.30	0.10	0.30
married	0.81	0.39	0.77	0.42	0.75	0.43	0.72	0.45	0.72	0.45
single parent	0.04	0.19	0.05	0.22	0.05	0.21	0.05	0.22	0.06	0.23
real family income	$32,194	18,612	$34,934	29,689	$39,621	32,772	$49,504	54,999	$50,183	83,350
real labour income, head	$21,353	14,871	$22,578	16,089	$24,824	24,007	$29,364	37,439	$29,429	50,584
real labour income, wife	$3,584	6,113	$5,240	7,626	$8,051	10,871	$10,075	18,377	$10,402	14,850
total real food expenditure	$4,945	2,401	$4,351	2,178	$4,059	2,239	$4,141	2,239	$4,136	2,396
real food expenditure, home			$3,404	1,851	$3,087	1,946	$2,833	1,635	$2,780	1,687
real food expenditure, away from home			$900	1,034	$943	915	$1,277	1,224	$1,304	1,434
real home value	$14,536	13,819	$45,071	48,002	$78,713	103,848	$133,332	178,776	$195,349	260,407
real net non housing wealth			$83,487	442,372	$94,317	306,501	$120,599	652,103	$136,203	647,551
real net wealth including housing			$116,819	455,379	$128,413	333,071	$161,730	688,252	$193,296	696,897
home owner	0.72	0.45	0.71	0.45	0.70	0.46	0.76	0.43	0.76	0.43
annual hours worked, head	2,214	717	2,153	699	2,246	647	2,140	628	2,178	758
annual hours worked, wife	531	782	727	859	988	957	1,009	975	1,040	1,020
unemployed	0.01	0.12	0.03	0.16	0.02	0.16	0.03	0.17	0.03	0.16
on welfare	0.03	0.17	0.04	0.20	0.02	0.14	0.02	0.13	0.04	0.18
observations	1415		2101		2361		2863		2948	

Note: Wealth information is for 1983, 1993, 2000, 2004. Price data for food at home and away from home is available starting 1978.

A2: Summary statistics: real family income vs. real food expenditure by quintile for the liquidity unconstrained.

	y≤20	20>y≥40	40>y≥60	60>y≥80	y>80	y≤20	20>y≥40	40>y≥60	60>y≥80	y>80
			Real Family Income					Real Food Expenditure		
1970	12,319	22,026	29,460	37,804	59,396	3,300	4,247	4,804	5,474	6,904
	(3,982)	(2,357)	(2,133)	(2,834)	(20,496)	(1,768)	(1,636)	(2,013)	(2,152)	(2,654)
1980	12,285	22,197	30,460	40,006	69,904	2,803	3,742	4,427	4,857	5,970
	(4,076)	(2,388)	(2,320)	(3,535)	(49,350)	(1,631)	(1,654)	(1,833)	(1,961)	(2,356)
1990	12,601	23,840	33,674	45,594	82,451	2,683	3,477	3,896	4,729	5,512
	(4,576)	(2,910)	(3,039)	(3,823)	(49,355)	(1,518)	(1,595)	(1,584)	(2,712)	(2,360)
2000	11,846	24,131	35,469	49,972	109,082	2,898	3,320	3,891	4,475	5,593
	(5,031)	(3,077)	(3,516)	(5,382)	(88,471)	(1,993)	(1,764)	(1,749)	(1,861)	(2,564)
2004	11,504	23,756	35,408	49,434	111,973	2,698	3,505	3,856	4,404	5,629
	(4,500)	(3,433)	(3,434)	(5,031)	(155,326)	(1,597)	(1,784)	(1,743)	(2,327)	(2,929)
			Real Net Non Housing Wealth					Real Net Wealth including Housing		
1983	25,533	26,080	46,917	100,559	217,450	37,739	43,863	75,160	138,271	287,880
	(89,388)	(54,734)	(256,992)	(612,163)	(706,571)	(96,025)	(66,456)	(268,761)	(617,496)	(724,826)
1993	61,497	43,317	42,421	82,208	241,619	77,035	65,613	68,669	120,679	309,215
	(334,796)	(207,569)	(76,895)	(148,147)	(509,582)	(346,775)	(243,601)	(100,715)	(159,233)	(545,802)
2000	37,434	43,993	60,791	88,479	324,234	52,706	65,304	89,308	129,941	410,559
	(148,632)	(113,414)	(161,677)	(363,260)	(1,271,468)	(154,977)	(129,980)	(178,839)	(381,668)	(1,332,628)
2004	28,492	64,597	81,760	102,169	345,840	44,574	90,787	119,872	155,885	475,433
	(95,680)	(303,799)	(243,655)	(270,951)	(1,239,187)	(112,169)	(314,627)	(269,987)	(290,241)	(1,319,365)
			SHARE OF NONWHITE WITHIN NONWHITE IN QUINTILE					SHARE WITH EDU<13 WITHIN QUINTILE		
1970	0.31	0.21	0.21	0.09	0.17	0.95	0.83	0.76	0.63	0.54
1980	0.26	0.29	0.16	0.18	0.11	0.75	0.62	0.51	0.47	0.31
1990	0.33	0.30	0.19	0.09	0.10	0.70	0.56	0.48	0.31	0.18
2000	0.25	0.25	0.18	0.21	0.11	0.63	0.58	0.50	0.32	0.17
2004	0.26	0.20	0.16	0.25	0.14	0.62	0.57	0.48	0.34	0.15

Note: Quintiles are computed on real family income for each available year of data, and includes negative or zero values.

A3. Euler Equation Estimation: OLS vs. LSDV

VARIABLES	OLS				LSDV			
	all		unconstrained		all		unconstrained	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age	0.001	0.000	0.000	-0.000	0.001	0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Age squared	-0.000*	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
change in number of adults	0.124***	0.124***	0.127***	0.127***	0.121***	0.121***	0.123***	0.123***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
change in number of kids	0.105***	0.105***	0.104***	0.104***	0.104***	0.104***	0.104***	0.104***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
change in marital status	-0.033***	-0.033***	-0.035***	-0.035***	-0.035***	-0.035***	-0.034***	-0.034***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
change in num hours worked, head	0.003***	0.003***	0.003***	0.003***	0.003**	0.003**	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
change in num hours worked, wife	0.017***	0.017***	0.017***	0.016***	0.015***	0.015***	0.014***	0.014***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
income volatility	-0.006	-0.006	-0.005	-0.005	0.004	0.004	0.006	0.005
	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
change in real house value	0.026***	0.026***	0.021***	0.021***	0.026***	0.026***	0.021***	0.021***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
change in rentalship	0.050**	0.050**	0.055***	0.055***	0.044**	0.044**	0.048**	0.048**
	(0.020)	(0.020)	(0.021)	(0.021)	(0.022)	(0.022)	(0.024)	(0.024)
change in ownership	0.056	0.055	0.123	0.122	0.047	0.048	0.159*	0.160*
	(0.075)	(0.075)	(0.079)	(0.079)	(0.084)	(0.084)	(0.089)	(0.089)
change in real rent	0.032***	0.032***	0.034***	0.034***	0.033***	0.033***	0.039***	0.039***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
ln(real interest rate, h)	0.112**	0.021	0.130**	0.053	0.112	0.136*	0.129	0.152*
	(0.053)	(0.065)	(0.059)	(0.071)	(0.072)	(0.081)	(0.079)	(0.088)
price differential		0.011***		0.010**		-0.018		-0.017
		(0.004)		(0.004)		(0.019)		(0.020)
estimated Pr(wealth>0)			0.046**	0.051**			0.020	0.021
			(0.021)	(0.021)			(0.039)	(0.039)
Constant	0.018	-0.026	-0.014	-0.054	0.025	0.073	-0.037	0.009
Observations	42973	42973	37730	37730	42973	42973	37730	37730
R-squared	0.051	0.051	0.053	0.053	0.121	0.121	0.134	0.134
Number of pid	5320	5320	4936	4936	5320	5320	4936	4936

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A4: Euler Equation Estimation: Arellano-Bond (AB) GMM

VARIABLES	all		unconstrained			
	(1)	(2)	(3)	(4)	(5)	(6)
Age	0.001	-0.008	0.001	0.011	-0.006	0.003
	(0.009)	(0.010)	(0.009)	(0.009)	(0.010)	(0.011)
Age squared	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
change in number of adults	0.091***	0.089***	0.089***	0.102***	0.089***	0.095***
	(0.029)	(0.029)	(0.031)	(0.032)	(0.031)	(0.032)
change in number of kids	-0.024	0.006	-0.019	0.028	0.001	0.018
	(0.077)	(0.074)	(0.079)	(0.080)	(0.075)	(0.075)
change in marital status	-0.074***	-0.069***	-0.067**	-0.056**	-0.065**	-0.060**
	(0.027)	(0.026)	(0.027)	(0.027)	(0.027)	(0.027)
change in num hours worked, head	-0.002	-0.002	-0.001	-0.001	-0.001	-0.001
	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
change in num hours worked, wife	0.059***	0.058***	0.046***	0.045**	0.043**	0.043**
	(0.016)	(0.016)	(0.018)	(0.018)	(0.018)	(0.018)
income volatility	0.059	0.086	0.046	0.020	0.068	0.081
	(0.062)	(0.062)	(0.064)	(0.065)	(0.063)	(0.071)
change in real house value	0.048*	0.055**	0.050	0.048	0.052*	0.051
	(0.029)	(0.027)	(0.033)	(0.032)	(0.031)	(0.031)
change in rental status	0.011	0.006	-0.013	-0.009	-0.014	-0.024
	(0.058)	(0.058)	(0.064)	(0.066)	(0.065)	(0.064)
change in ownership	0.458	0.460	0.520	0.588	0.600*	0.493
	(0.337)	(0.296)	(0.397)	(0.412)	(0.353)	(0.350)
change in real rent	0.115***	0.124***	0.124**	0.134**	0.137**	0.122**
	(0.041)	(0.042)	(0.053)	(0.060)	(0.053)	(0.055)
ln(real interest rate, h)	1.778	1.353	1.250	1.735*	1.323*	1.178
	(1.256)	(0.837)	(1.222)	(1.034)	(0.789)	(0.748)
price differential		0.131			0.134	0.161
		(0.094)			(0.093)	(0.132)
estimated Pr(wealth>0)				-0.116		0.285
				(0.333)		(0.304)
Observations	33965	33965	29931	29491	29931	29491
R-squared						
Number of pid	4695	4695	4363	4255	4363	4255
Arrelano-Bond test for AR(1)	-33.11	-33.50	-32.68	-31.63	-32.87	-31.06
Pr>z	0	0.195	0.259	0.363	0	0
Arrelano-Bond test for AR(2)	12.61	12.70	12.41	11.19	12.42	11.15
Pr>z	0	0	0	0	0.270	0.345
Arrelano-Bond test for AR(3)	-1.301	-1.297	-1.128	-0.911	-1.103	-0.943
Pr>z	0.193	0	0	0	0	0
Sargan test of overid	20.79	18.14	19.09	21.89	16.82	20.33
df	13	14	13	14	14	15
Prob>chi2	0.0772	0.200	0.120	0.364	0.693	0.544
Hansen test of overid	13.63	11.97	12.74	15.21	10.92	13.76
df	13	14	13	14	14	15
Prob>chi2	0.401	0.609	0.468	0.0809	0.266	0.160
Number of Instruments	32	34	32	34	34	36
F-stat	6.069	6.202	4.507	4.194	4.586	4.096
Prob>F	0	0	2.56e-10	1.10e-09	5.05e-11	1.01e-09
Avg num obs	7.234	7.234	6.860	6.931	6.860	6.931
max num obs	19	19	19	19	19	19

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A5: Volatilty of real family income and real food expenditure, biennial samples

VARIABLES	food (1)	income (2)	food (3)	income (4)	food (5)	income (6)	food (7)	income (8)	food (9)	income (10)
year/1000	0.898***	3.323***	0.945***	3.329***	0.567**	4.001***	0.605***	4.080***	2.050***	2.460***
	(0.161)	(0.250)	(0.159)	(0.243)	(0.272)	(0.429)	(0.224)	(0.347)	(0.344)	(0.359)
nonwhite * year/1000	0.719	1.211								
	(0.605)	(0.802)								
single parent * year/1000			0.177	2.614**						
			(0.842)	(1.154)						
continuously married * year/1000					0.354	-1.261**				
					(0.331)	(0.509)				
years of education<13 * year/1000							0.945***	-1.003**		
							(0.322)	(0.480)		
1st income quintile * year/1000									-1.531**	8.554***
									(0.666)	(1.299)
2nd income quintile * year/1000									-0.953*	1.181*
									(0.517)	(0.624)
4th income quintile * year/1000									-1.076**	-0.906*
									(0.449)	(0.478)
5th income quintile * year/1000									-0.734	0.900
									(0.454)	(0.551)
nonwhite	-1.391	-2.383								
	(1.203)	(1.591)								
single parent			-0.321	-5.144**						
			(1.674)	(2.290)						
continuously married					-0.756	2.446**				
					(0.657)	(1.011)				
years of education<13							-1.871***	2.015**		
							(0.639)	(0.952)		
1st income quintile									3.131**	-16.732***
									(1.323)	(2.577)
2nd income quintile									1.912*	-2.310*
									(1.026)	(1.237)
4th income quintile									2.130**	1.793*
									(0.891)	(0.949)
5th income quintile									1.451	-1.742
									(0.901)	(1.094)
change in quintile									0.009***	-0.018***
									(0.002)	(0.005)
Constant	-1.654***	-6.435***	-1.744***	-6.447***	-0.961*	-7.745***	-1.070**	-7.949***	-3.952***	-4.773***
	(0.320)	(0.497)	(0.315)	(0.482)	(0.541)	(0.851)	(0.445)	(0.690)	(0.682)	(0.713)
Observations	39365	39365	39425	39425	39425	39425	39163	39163	37787	37787
R-squared	0.002	0.006	0.001	0.007	0.009	0.011	0.001	0.007	0.013	0.059

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A6: Black-White Divide

	1983		1993		2000		2004	
	white	nonwhite	white	nonwhite	white	nonwhite	white	nonwhite
Nonhousing wealth less than 2	0.17	0.40	0.15	0.30	0.20	0.33	0.19	0.30
months of family income	(0.38)	(0.49)	(0.36)	(0.46)	(0.40)	(0.47)	(0.39)	(0.46)
Real family income	$36,715	$26,342	$44,088	$29,993	$51,513	$33,091	$52,294	$34,520
	(27,034)	(16,261)	(46,967)	(38,640)	(56,987)	(28,719)	(87,842)	(27,793)
Real nonhousing net wealth	$89,305	$19,312	$99,087	$34,838	$129,727	$40,359	$145,185	$62,950
	(461,325)	(46,061)	(317,085)	(76,817)	(686,513)	(114,193)	(675,682)	(339,143)
Real net wealth, including housing	$123,872	$38,834	$134,814	$52,999	$173,283	$60,524	$206,313	$86,360
	(474,430)	(73,288)	(344,264)	(100,867)	(724,021)	(134,658)	(727,563)	(348,761)

Standard deviation in parentheses